Least-Squares Monte Carlo Methods for Proxy Modeling of Life Insurance Companies

Ralf Korn (TU Kaiserslautern, Fraunhofer ITWM)
Based on:

See also

More references:
later
A motivating problem: Solvency II requirements


Article 122:
“Where practicable, insurance and reinsurance undertakings shall derive the solvency capital requirement directly from the probability distribution forecast generated by the internal model of those undertakings, using the Value-at-Risk measure set out in Article 101(3).”
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• Least-Squares Monte Carlo approach
1 Least Squares Monte Carlo: Basic idea

A simpler task: Derive the distribution of an option price $g(X(t))$ at time $t$ with a payment of $H = h(X(T))$ at time $T$

Challenge: There is no closed-form representation of $g(X(t))$
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  - Derive a regression representation \( r(X(t)) \) for \( g(X(t)) \) on the basis of \( h(X(T)) \)
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  - Derive a regression representation $r(X(t))$ for $g(X(t))$ on the basis of $h(X(T))$
  - Simulate a huge number of representative values $X(t)$ to obtain an approximation of the distribution function for $g(X(t))$ with the help of $r(X(t))$
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- Least-squares MC: $X(t)$  $X(T)$
1 Least Squares Monte Carlo: A simple option pricing example

European call option: Derive the distribution of a European call option price $g(S(1))$ at time 1 with a payment of $H = (S(2) - K)^+$ at time 2 by using a linear, a quadratic and a cubic regression function (still linear in the parameters!)
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**European call option**: Derive the distribution of a European call option price $g(S(1))$ at time 1 with a payment of $H = (S(2) - K)^+$ at time 2 by using a linear, a quadratic and a cubic regression function (still linear in the parameters!): Modified linear function
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Replication approach: Derive the distrib. of a Eur. call price $g(S(1))$ at time 1 with a payment of $H = (S(2) - K)^+$ at time 2, use a lin., a quadr. and a cubic regression function for $H$ (!!!) at $t=2$ and then calculate its price at $t=1$ => slightly better than LSMC
1 Least Squares Monte Carlo: Main tasks/problems

Theoretical justification:

- Convergence results
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Practical implementation:

- Choice of the regression function
- Number of simulation runs for calibration
- How to choose the fitting values?
- How to choose the calibration values?
- How to judge the performance of the model?
1 Least Squares Monte Carlo: Convergence results

Theoretical justification: Convergence results => two convergence issues

Theorem:
Let \( F(X) = E(Y|X) \) be a functional of \( X \) that is in \( L^2 \). Consider a set of \( K \) linearly independent basis functions \( e_k(x) \) with \( e_0(x) = 1 \), the projection

\[
\hat{F}^{(K)}(X) = \sum_{k=0}^{K-1} \beta_k e_k(X)
\]

of \( F(X) \) on the basis functions and

\[
\hat{F}^{(K,N)}(X) = \sum_{k=0}^{K-1} \hat{\beta}^{(N)}_k e_k(X)
\]

its approxim. with the LS-estimators of the coefficients based on \( N \) realizations of \( Y \). 

a) If the family of basis functions is complete in \( L^2(IR^d,B^d,P) \) then we have

\[
\hat{F}^{(K)}(X) \xrightarrow{K \to \infty} F(X) \ \text{in} \ \ell^2(IR^d,B^d,P)
\]

b) \[
\hat{F}^{(K,N)}(X) \xrightarrow{N \to \infty} \hat{F}^{(K)}(X) \ \text{a.s.}
\]
2 Least Squares Monte Carlo: Aspects of application

Necessary ingredients for calculating the loss distribution at a future time:
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Necessary ingredients for calculating the loss distribution at a future time:

- A cash flow projection (CFP) method/tool for generating market consistent future scenarios of the incomes/outflows, decisions, ... of a life insurance company over a projection horizon (Note: one simulation run is computationally extremely expensive)
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- A simulation concept how to cover the relevant (!) values of the risk factors (i.e. the ones that are relevant for the loss distribution and for the distribution at the calculation time)
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- A simulation concept how to cover the relevant (!) values of the risk factors (i.e. the ones that are relevant for the loss distribution and for the distribution at the calculation time)

- A decision on the method to actually determine the loss distribution and in particular the relevant high/low quantiles for the Solvency Capital Requirements
2 Least Squares Monte Carlo: Aspects of application – 2

The necessary key steps/decisions/ingredients of the LSMC approach on the way to a reliable proxy modelling for a life insurance company:

- a detailed description of the simulation setting and the required task
- a concept for a calibration procedure for the proxy function
- a validation procedure for the obtained proxy function
- the actual application of the LSMC model to forecast the full loss distribution
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First part:
Given by the CFP method and by the SCR requirement/definition, in particular by specifying the risk factors $X = (X_1, ..., X_d)$ the insurer is exposed to in the next year.

A realization of $X$ under the subjective measure $P$ is called an outer scenario (i.e. one possibility how the world will evolve during that year.)
3 LSMC-Proxy Modelling: Simulation setting and the task

The task(s):

- Calculate the (full) loss distribution of a life insurance company (over a given time horizon) at the end of the year
- From this derive the SCR as the 99.5% quantile (of the difference of the available capital at time 1 and at time 0: $B_1 AC_1 - AC_0$)
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The simulation setting:

- Simulate realizations of risk factors $X$ at time 1 under $P$
- For each realization of the risk factors derive the (discounted) available capital at time 1:
  \[
  AC(X) = E_Q \left( \sum_{t=1}^{T} B_t^{-1} Z_t | X \right) =: E_Q \left( \sum_{t=1}^{T} z_t \left( \phi_t(X) \right) | X \right)
  \]
  where $Z_t$ denotes the net profit at time $t$ and let $T$ mark the projection end. Note that we simulate now, i.e. we use the CFP method available now!
3 LSMC-Proxy Modelling: Simulation setting and the task – 2

An example

<table>
<thead>
<tr>
<th>Component</th>
<th>Risk Factor Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>Risk-free interest rates movement</td>
</tr>
<tr>
<td>$X_2$</td>
<td>Change in interest rate volatility</td>
</tr>
<tr>
<td>$X_3$</td>
<td>Change in equity volatility</td>
</tr>
<tr>
<td>$X_4$</td>
<td>Shock on volatility adjustment (if used by the company)</td>
</tr>
<tr>
<td>$X_5$</td>
<td>Credit default</td>
</tr>
<tr>
<td>$X_6$</td>
<td>Credit spread widening</td>
</tr>
<tr>
<td>$X_7$</td>
<td>Currency exchange rate risk</td>
</tr>
<tr>
<td>$X_8$</td>
<td>Shock on equity market value</td>
</tr>
<tr>
<td>$X_9$</td>
<td>Shock on property market value</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>Lapse stress on best estimate assumptions</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>Mortality catastrophe stress with a one-off increase in mortality</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>Mortality trend volatility stress</td>
</tr>
<tr>
<td>$X_{13}$</td>
<td>Mortality level stress on best estimate assumptions</td>
</tr>
<tr>
<td>$X_{14}$</td>
<td>Longevity trend volatility stress on best estimate assumptions</td>
</tr>
<tr>
<td>$X_{15}$</td>
<td>Longevity level stress on best estimate assumptions</td>
</tr>
<tr>
<td>$X_{16}$</td>
<td>Morbidity stress on best estimate assumptions</td>
</tr>
<tr>
<td>$X_{17}$</td>
<td>Expenses stress on best estimate assumptions</td>
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</tbody>
</table>

- Capital market shocks
- Actuarial risks
3 LSMC-Proxy Modelling: Simulation of the outer and inner scenarios

Generate the outer scenarios (the **fitting points**) under $P$, i.e.

- have a **stochastic model** for each risk $X_i$ and simulate realizations $X^{(k)}$ of $X$,
- use a **large number** of outer scenarios (or have a strategy how to fill the range of the risks)
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Generate the outer scenarios (the **fitting points**) under $P$, i.e.

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- use a **large number** of outer scenarios (or have a strategy how to fill the range of the risks)

Generate the corresponding inner scenarios (the **fitting values**) under $Q$, i.e.

- use an **economic scenario generator** (ESC) for generating very few (typically 1 or 2) market consistent scenarios $\phi^{(k,j)}(X^{(k)})$ for each outer scenario
- derive the **fitting values** $Y^{(k)}$ via

$$Y^{(k)} = \frac{1}{a} \sum_{j=1}^{a} Y^{(k,j)} = \frac{1}{a} \sum_{j=1}^{a} \sum_{t=1}^{T} z_t \left( \phi^{(k,j)}(X^{(k)}) \right)$$
3 LSMC-Proxy Modelling: Calibrating the proxy function

Note: Pairs \((X^{(k)},Y^{(k)})\) for setting up a regression function are now available

Main question: How to choose the regression function?
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Suggestion:
Use monomials of the type
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e_k(x) = (x_1)^{j_1} \cdot \ldots \cdot (x_d)^{j_d}
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at step \(k\) of the algorithm used to choose the monomials.
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Find the least-squares optimal coefficients based on the \(N\) fitting points and fitting values to obtain the proxy function by solving

\[
\hat{\beta}^{(N)} = \arg \min_{\beta \in \mathbb{R}^K} \left\{ \sum_{i=1}^{N} \left( Y^{(i)} - \sum_{k=0}^{K-1} \beta_k e_k \left( X^{(i)} \right) \right)^2 \right\}
\]
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Algorithm/principle for choosing the monomials in Krah et al. (2018):

Principle of marginalization
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Example of choice by marginalization:

$x_1^2 x_2$ can only be among the candidates if $x_1^2, x_1 x_2, x_1, x_2$ are already choosen
3 LSMC-Proxy Modelling: Validating the proxy function

Before the proxy function can be used for the actual simulation of the distribution of the Available Capital:

- Check if the proxy function based model delivers correct values!
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Some out of-sample-tests are described in Krah et al. (2018)
4 A Numerical Example with LSMC-Proxy Modelling

Actual use of the proxy function

- Simulate many outer scenarios (i.e. 131072 real world scenarios)
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**References**


